

ASSESSMENT OF VENTRICLE VOLUME FROM SERIAL MRI SCANS IN COMMUNICATING HYDROCEPHALUS

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ABSTRACT

Postoperative communicating hydrocephalus has been recognized in patients with brain tumors. The associated changes in ventricle volume can be difficult to identify, particularly over short time intervals. Potentially, accurate ventricle volume estimates could provide for a better understanding of communicating hydrocephalus, and lead to more confident diagnoses. Our method evaluates ventricle size from serial brain MRI examinations, we 1) combined serial images to increase SNR 2) segmented this image to generate a ventricle template using fast marching methods and geodesic active contours, and 3) propagate the segmentation using deformable registration of the original MRI datasets. By applying this deformation to the ventricle template, serial volume estimates were obtained in a robust manner.

INDEX TERMS: Brain imaging, MRI, brain tumor, hydrocephalus, segmentation, registration, monitoring.

1. INTRODUCTION

Serial brain MRI examinations are performed to monitor tumor size in patients with such brain lesions. The routine use of high resolution 3D imaging and coregistration facilitates such evaluation. In addition, the routine clinical observation of such coregistered studies suggests that ventricle size progressively increases in many of these patients. This is a poorly documented phenomenon, likely representing a communicating hydrocephalus [4]. The etiology is unclear, and is possibly related to the introduction of blood and proteins into the cerebral-spinal fluid (CSF) during surgery.

The change in ventricular size may be quite subtle even by comparison of coregistered images. Thus, it is desirable to identify the incidence of the phenomenon, and to correlate the presence or absence of such a phenomenon with clinical symptoms. Therefore, we sought an objective method to

systematically characterize the clinical observation of progressive ventriculomegaly in this group.

In previous work, ventricles were segmented using region-growing combined with anatomical knowledge [9] in images of high quality. Holden et al. [2] used non-rigid registration combined with data from an atlas to segment brain ventricles, relying on the high performance of the registration algorithm. The registration with an atlas is also addressed in [6] using an expectation-maximization joint model. Most recently, Hu and Collins [3] proposed a model-based segmentation on multi-modality MR images.

Many prior studies deal with high resolution data from uniform data sets. Because our data comes from patients with brain tumors on a number of different imaging platforms, image contrast can be quite variable and signal-to-noise ratio (SNR) low. Therefore, our method was designed to exploit patient-specific data for better-adapted intra-patient non-rigid registration, less sensitive to image quality and the anatomical variability of brain tumor patients. Mean T1 images with increased SNR provide the input for the fine segmentation based on geodesic active contours. Hence, no correction for inhomogeneous signal intensity is required. Finally, the mean ventricular shape is adaptively propagated through the temporal data to quantify size changes.

2. METHOD

Data acquisitions

Patients with brain tumors evaluated at the Clinical Center of the NIH were scanned on 1.5 T GE (Milwaukee, WI) or 3 T Philips (Best, Netherlands) MR systems at approximately 1 to 3 month intervals. As part of the routine clinical imaging, 3D T1 weighted sequences were obtained following injection of an intravenous contrast agent. On the 1.5 T scanner a 3D SPGR technique was used with TR 12 ms; TE 5 ms; flip angle 20 degrees; 240 cm FOV; 256 matrix sagittal acquisition, 152 slices 2 mm thick with 1 mm overlap. On the 3.0 T scanner the parameters were TR 5 ms;

TE 2 ms; flip angle 15 degrees, 240 cm FOV, 256 matrix; 1 mm slice thickness (no overlap).

Preprocessing

For each patient, the 3D datasets were coregistered to the first dataset in the series using FLIRT (FMRIB, Oxford, UK) under MEDx (Medical Numerics, Sterling, VA). Coregistration was done by a 6 parameter rigid body transformation (translation + rotation) using a least squares cost function. To normalize the dataset, a large $\sim 100 \text{ cc}^3$ volume of interest (VOI) was automatically placed in the brain volume in relation to its center of mass. The histogram of this VOI was used to identify the modal signal intensity, presumably representing white matter. Each dataset was normalized by dividing by this value, and a high SNR “mean” image was generated for each patient by averaging the time point datasets using AFNI (<http://afni.nimh.nih.gov/>). Finally, smoothing was performed by anisotropic diffusion [5].

Segmentation

The second stage of the method is the segmentation of lateral ventricles and our approach uses a combination of fast marching and geodesic active contour level sets [1,8]. The fast marching method assumes that the surface can only expand starting from the seed point. The seed is provided by the user on the septum pellucidum (between the bodies of the lateral ventricles), as shown in Figure 1. The speed of expansion is constant and along the surface normal n . The MRI scan I provides the feature image, while the sigmoid of the gradient of I supplies the speed function I_e . The first segmentation given by the fast marching level set is I_f .

$$\frac{dI_f}{dt} + \vec{n} I_e \nabla I_f = 0$$

A better-adapted level set based on geodesic active contours is used to refine the fast marching segmentation [1]. To initialize the model, we use the fast marching segmentation as input level image (zero-level) into the geodesic active contour I_L . The weights w_1 , w_2 and w_3 control respectively the speed c , curvature k and attraction to edges (Caselles et al. 1997).

$$\frac{dI_L}{dt} = I_e (w_1 c + w_2 k) |\nabla I_L| + w_3 \nabla I_e \nabla I_L$$

Propagation

A refinement of the intra-patient registration is required to compensate for the residual deformation not covered by the rigid registration used in preprocessing. Differences in the

brain anatomy are mainly due to effects of therapeutic interventions, such as surgery and chemotherapy as well as disease progression (e.g. tumor growth or hydrocephalus). We propose employing the non-rigid registration algorithm based on B-splines [7].

The deformation of objects is governed by an underlying mesh of control points in coarse to fine multiresolution approach. B-splines allow to locally control the deformation T and by varying the spacing between control points, the number of degrees of freedom is adapted to account for more global (affine) or local (non-rigid) transforms. Finally, a compromise between the similarity provided by mutual information M [10] and smoothing S is searched, where $p(I, J)$ is the joint probability distribution of images I and J , and $p(I)$ and $p(J)$ their marginal distributions. For more detail on the B-spline definition of the transformation T , please refer to [7].

$$\begin{aligned} \arg \min [M(I | T(I)) - S(T)] \\ M(I | J) &= \frac{p(I) + p(J)}{p(I, J)} \\ S(T) &= \int_{x,y,z} (\partial^2 T)_{x,y,z} dx dy dz \end{aligned}$$

The resulting deformation fields between the mean image and the temporary acquisitions of each patient are applied to the ventricle mask segmented from the mean image using a nearest-neighbor interpolation. The deformations are intra-patient and well defined, and provide a robust propagation of the segmentation.

These processes were implemented under Visual C++ 8.0 (Microsoft), OpenGL (SGI) and the Insight Segmentation and Registration Toolkit (ITK) 2.4 (Kitware, Inc.).

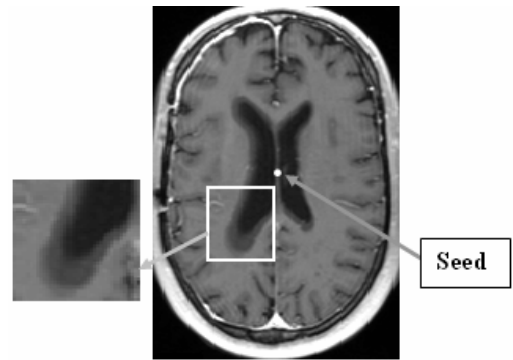


Figure 1: The position of the user specified seed to initiate the ventricle segmentation on the mean image. Note the intermediate intensity of the tissue adjacent to the posterior portion of the body of the right lateral ventricle. This is due to the averaging of datasets at varying stages of ventricle dilation in this location.

3. RESULTS

Ventricle size was analyzed from six patients who were imaged with MRI between 8 and 25 times at one to three month intervals over a maximum of 3 years. The total number of time-point scans was 95. The results of the semi-automated assessment method of ventricles from the T1 brain MRI are shown in Figure 2. The MRI represents the mean image resulting from rigid transformation, intensity normalization and averaging. This mean image has increased the signal-to-noise ratio (SNR) as compared to a single scans (Figure 3). Subsequently, the lateral ventricles were segmented from the mean data, using fast marching and geodesic active contour level sets, as seen in Figure 2.

To obtain the segmentation of ventricles on each scan of the time series, the mean image was registered to each individual scan of the same patient by non-rigid registration and the deformation fields were saved. This deformation field was then applied to the ventricle mask, thereby propagating the segmentation through each individual time point of the series. An example of the robustness of the 3D segmentation of ventricles across the entire series of a patient's temporal acquisition is shown in Figure 3. Results in the axial plane of temporal scans of a different patient are then presented in Figure 3.

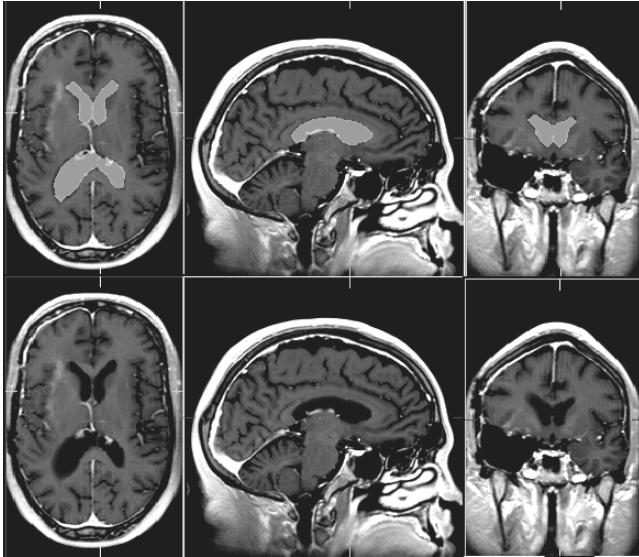


Figure 2: The 3D segmentation of brain ventricles from the mean image. Note the improved signal-to-noise-ratio (SNR) of the mean image, compared to SNR of data in Figure 3.

For the quantification of segmentation/propagation results, we compared the data processed by our algorithm with manually-segmented data. A total of 15 individual MRI scans from 3 patients were analyzed (5 acquisitions/patient) and the manually measured volumes of the lateral ventricles were recorded. Figure 5 presents the temporal evolution of

the automatically evaluated ventricular changes near the manually measured volumes (in mm^3). The mean error in volume estimation is of 3.58% with a standard deviation of 3.66.

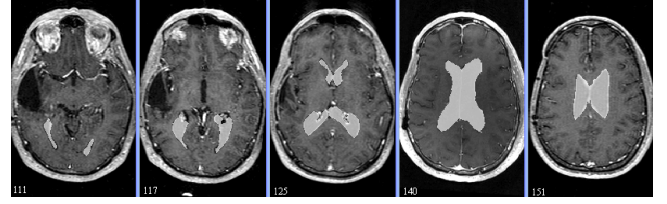


Figure 3: The 3D segmentation of brain ventricles from a single time point of a patient.

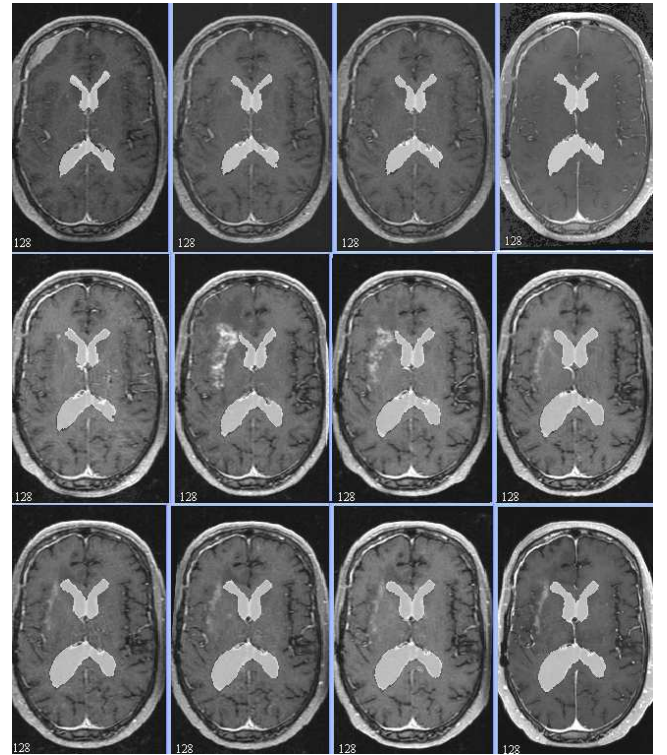


Figure 4: Twelve coregistered MRI sets obtained at 1-3 month intervals demonstrating the change in ventricle size over time, and the segmentation obtained. The initial MRI is top left, and the final MRI is Bottom right. The segmentation results correlate well with the steady increase in ventricular volume and change of ventricular shape. Note that there is considerable variation in image contrast due to changes in tumor and differences in scanners used.

5. DISCUSSION

The segmentation results are robust throughout the database and the segmentation propagation based on the deformation

fields accurate, as confirmed by experienced radiologists. The initial results show great promise toward an automated reliable tool for ventricular size change assessment and confirmation of radiological observations related to the possible relation between brain tumor resection and communicating hydrocephalus.

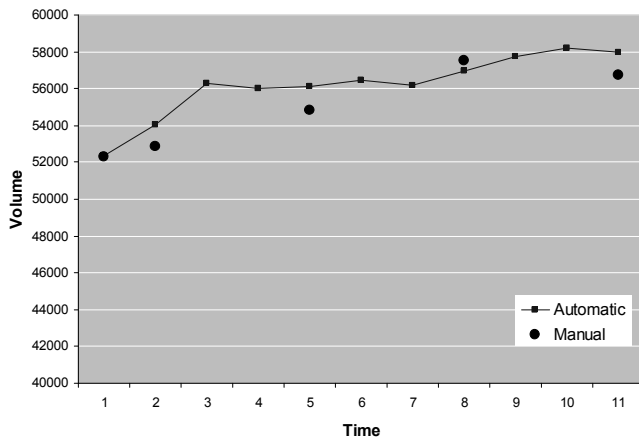


Figure 5: Manual versus semi-automatic ventricular size estimation. This example shows the automatic quantification of ventricular growth in a brain tumor patient, along the manual measurements of ventricular volume.

First, intra-patient data were registered using a rigid transformation and normalized in intensity. A mean image was computed from the normalized temporal scans of each patient, which has increased signal-to-noise ratio (SNR) than temporal scans. Subsequently, the lateral ventricles were segmented from the mean data, using fast marching and geodesic active contour level sets. The mean image was registered to each temporal scan of the same patient by non-rigid registration and the deformation fields were saved. Using the ventricle mask and the deformation fields, the segmentation was propagated through the temporal scans.

There are several advantages to this technique. Because the segmentation is initially performed on a high SNR dataset is used to define the ventricles in all the component data sets, it is not necessary for the segmentation to be successful on each individual dataset. Therefore an individual dataset which is noisy or artefact ridden (e.g. from patient motion) can be evaluated. Furthermore, disruption of the ventricle border due to surgical intervention or tumor growth may cause region growing or level set segmentation to “leak out” of the ventricular system. In this method, this needs only be dealt with on the mean data set and not on each individual data set.

The main disadvantage of this technique is the computational overhead, prohibitive for the routine clinical use of such methods. Its reduction will be addressed in future work. A larger database and an extended evaluation of the method will follow. The algorithm will allow the distinction between cases that show an increase in

ventricular size and those without hydrocephalus. Further development will lead to a fully-automated assessment method ready to be used in daily clinical practice and support the documentation of the tumor related brain atrophy.

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